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Attention-Inspired Artificial Neural Networks for Speech Processing: A Systematic Review

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Abstract: Artificial Neural Networks (ANNs) were created inspired by the neural networks in the human brain and have been widely applied in speech processing. The application areas of ANN include: Speech recognition, speech emotion recognition, language identification, speech enhancement, and speech separation, amongst others. Likewise, given that speech processing performed by humans involves complex cognitive processes known as auditory attention, there has been a growing amount of papers proposing ANNs supported by deep learning algorithms in conjunction with some mechanism to achieve symmetry with the human attention process. However, while these ANN approaches include attention, there is no categorization of attention integrated into the deep learning algorithms and their relation with human auditory attention. Therefore, we consider it necessary to have a review of the different ANN approaches inspired in attention to show both academic and industry experts the available models for a wide variety of applications. Based on the PRISMA methodology, we present a systematic review of the literature published since 2000, in which deep learning algorithms are applied to diverse problems related to speech processing. In this paper 133 research works are selected and the following aspects are described: (i) Most relevant features, (ii) ways in which attention has been implemented, (iii) their hypothetical relationship with human attention, and (iv) the evaluation metrics used. Additionally, the four publications most related with human attention were analyzed and their strengths and weaknesses were determined.

Keywords: artificial neural networks; deep learning; attention; speech; systematic review



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1. Introduction

The analysis and processing of signals generated by the human speech consists in identifying and quantifying some physical features from the signals in such a way that they can be used for different speech related applications like identification, recognition and authentication. In that sense, Artificial Neural Networks (ANNs) have been a valuable computational tool because of their effectiveness in speech processing. Using deep learning algorithms, ANNs try to mimic the behaviour of the human brain to perform the functionalities involved in speech processing and, to improve the results, some algorithms implement some type of attention.

Given the above, it is of interest to know the diverse research works published between 2000 and 2020 that use ANNs and that implement attention for speech processing. While there are some systematic reviews related to speech processing using Artificial Intelligence techniques, to our best knowledge are no systematic reviews focused on attention such as the one presented in this paper.

Therefore, the literature search for this review was conducted on the ACM Digital Library, IEEE Explorer, Science Direct, Springer Link, and Web of Science databases to identify studies in the field of speech processing that reported the use of ANNs with some type of attention included in the title and/or abstract. We present a comprehensive

and integrative update of the topic based on the main findings of 133 papers published between 2000 and 2020. This review aims to identify and analyze papers about the design and construction of neural networks that implement some speech processing attention mechanism. According to this objective, four research questions are presented:

- RQ1: In which way has attention been integrated in deep learning algorithms and its possible relationship with human auditory attention?
- RQ2: What are the features of the speech signals used?
- RQ3: What are the neural network models used in the research papers?
- RQ4: Which methods or metrics were used to evaluate the obtained results?

The main contributions of this systematic review are as follows: (i) to analyze neural network research works that have implemented attention for speech processing, and its hypothetical relation with human attention (cognitive processes), (ii) to identify the speech processing application areas that have been investigated more widely between 2000 and 2020, and (iii) to determine which are the main Artificial Intelligence algorithms that have been applied to speech processing.

This review was constructed following the steps of the PRISMA methodology [1] and it is organised as follows. Section 2 explains the background and related work. Section 3 presents in detail the implementation of the PRISMA methodology for the systematic review process. Section 4 reports the results obtained from the application of the PRISMA methodology and presents the answers to the research questions. Section 5 discusses the obtained results. Finally, conclusions and final remarks are presented in Section 6.

2. Background and Related Works

Audio analysis has been widely used to retrieve human speech for the purposes of identification or extraction. This process becomes more complex when there are other sounds included in addition to human speech, for example when there is more than one speech at a time. The audio analysis process becomes even more complex when noise is present. However, the human brain is capable of performing the task successfully, thanks to the attention process. On the other hand, in the area of Computer Science, Artificial Neural Networks that use deep learning algorithms have achieved outstanding results in speech processing.

2.1. Related Works

To date, there are related systematic reviews, overviews, and surveys that collect information from different architectures and deep learning models. These publications are: (i) the publications that gather information from deep learning models with attention mechanisms, and (ii) the publications that collect the information from deep learning models applied to speech signal processing.

In the publications that gather information about deep learning models with attention mechanisms, we can mention the work of Galassi et al. [2]. This work presented a systematic overview to define a unified model for attention architectures in Natural Language Processing (NLP), focusing on those designed to work with vector representations of textual data. The publication provides an extensive categorization of the literature, presents examples of how attention models can utilize prior information, and discuss ongoing research efforts and open challenges. It also demonstrates how attention could be a key element in injecting knowledge into the neural model to represent specific features or to exploit previously acquired knowledge, as in transfer learning settings. This publication restricts their analysis to attentive architectures designed to work just with vector representation of textual data.

Lee et al. [3] conduct a survey on attention models in graphs and introduce three intuitive taxonomies to group the available work based on the problem setting (the type of input and output), the attention mechanism type used, and the task (e.g., graph classification, link prediction). They mention the main advantages of using attention on graphs, like that the attention allows the model: (i) to avoid or ignore noisy parts of the graph, thus

improving the signal-to-noise (SNR) ratio; (ii) to assign a relevance score to elements in the graph to highlight aspects with the most task-relevant information; and (iii) to provide a way to make the results of a model more interpretable. This publication restricts their analysis to examining and categorizing techniques that apply attention only to graphs (the methods that take graphs as input and solve some graph-based problem).

Within the works related to deep learning models applied to speech signal processing, the most recent are Nassif et al. [4], and Zhang et al. [5]. The first is a systematic literature review that identifies and examines the information from 174 articles that implement deep neural networks in speech-related applications like automatic speech recognition, emotional speech recognition, speaker identification, and speech enhancement [4]. Although several areas of application are involved, attention is not an issue.

The second work reviews recently developed and representative deep learning approaches for tackling non-stationary additive and convolutional degradation of speech to provide guidelines for those involved in developing environmentally robust speech recognition systems [5]. The authors focused their review only on models related to speech recognition and applied to noisy environments. Therefore, they do not consider other application areas.

Our systematic review differs from the existing studies because it identifies and analyzes publications about the design and construction of neural networks that implement some attention mechanism for speech processing.

2.2. Attention

According to cognitive psychology and neuroscience, attention can be identified as a cognitive activity that involves identifiable aspects of cognitive behavior [6,7]. In the literature, there are different definitions for the concept of -attention-, this is because it comprises several psychological and cognitive processes, which causes researchers from several fields to differ when it comes to having a definition that covers the different types of attention.

One of the definitions that possibly best describes attention is that of Richard Shiffrin [8], in which he mentions that attention refers to all those aspects of human cognition that the individual can control and to all those cognition aspects related to resource or ability limitations, including the methods to address such limitations. Thus, it is evident that the term attention is used to refer to different phenomena and processes, and not only among psychologists or neuroscientists but also in the everyday use of this term. Types of attention can be visual, auditory, and of sensory type; including conscious or unconscious attention.

Attention is not a single or unidirectional process, and it can be classified in terms of two different essential functions: (i) Top-Down attention, and (ii) Bottom-Up attention. Top-Down attention is a selective process that focuses cognitive resources on the most relevant sensory information to maintain a behavior directed to one or more objectives in the presence of multiple distractions. Top-Down attention implies the voluntary assignment of cognitive resources to an objective, while the other sensory stimuli are suppressed or ignored; this is why Top-Down attention is a process guided by objectives or expectations. Bottom-Up attention is a process triggered by unexpected or outstanding sensory stimuli, i.e., it refers to the orientation process of the attention guided purely by stimuli that are outstanding due to their inherent properties concerning the environment [9].

In the acoustic analysis, auditory attention is responsible for mediating perception and behavior, focusing sensory and cognitive resources on relevant information in the space of stimuli. Auditory attention is a selection process or processes that focuses the sensory and cognitive resources on the most relevant events in the soundscape. Stimulus-driven factors can modulate auditory attention in a Top-Down and Bottom-Up manner. Auditory attention samples sensory input and directs sensory and cognitive resources to the most relevant events in the soundscape [10].

2.3. Deep Learning and Neural Networks

Deep Learning is a subfield of Machine Learning that focuses on Artificial Neural Networks (ANNs) and the related algorithms to perform these networks' training. A deep learning model has at least two hidden layers of neurons (models that involve at least ten hidden layers are called Very Deep Neural Networks).

2.3.1. Artificial Neural Networks

Artificial Neural Networks (ANNs) are inspired by the functioning of neurons in the human brain. Inside the human brain each neuron receives stimuli and decides to activate itself or not. An activated neuron will send an electrical signal to other connected neurons, and then, if an extensive network of interconnected neurons is available, it is possible to learn to react to different inputs by adjusting the way they are connected and how sensitive they are to the stimuli [11].

While Artificial Neural Network models maintain the same principle of functioning of the human brain, they focus more on solving problems using data. A key component of a neural network is the neuron (also called a node). A node consists of one or more inputs (X_i), its weights (W_i), an input function (Z_i), an activation function (A_i), and an output (Y).

The input function takes the weighted sum of all the inputs, and the activation function uses the result to determine whether the node should be activated or not. The weights are adjusted during the learning process to amplify or reduce them according to the input data [11].

As a basis, the simplest structure is a single-layer neural network, and its main feature is that neurons belonging to the same layer cannot communicate. Next in complexity is the multi-layer neural network, where the first layer is called input layer, the last layer is called output layer, and the intermediate layers are called hidden layers.

The design and creation of deep neural networks involve the use of hyperparameters, which are parameters whose values are set and initialized prior to the training process of artificial neural network models, such as the number of layers in the neural network or the number of neurons in each layer. Some of the hyperparameters in deep neural network models are the following:

- Number of hidden layers
- Number of neurons in each layer
- Initialization weights
- The activation function
- The cost function
- An optimizer
- A learning rate

Deep learning comprises several types of artificial neural network architectures, including convolutional, recurrent, short-term and long-term memory, among others.

Convolutional Neural Networks (CNNs) is one of the most extensively used approaches for object recognition because their design is based on the visual cortex of animals. In convolutional neural networks, hidden layers of neurons are connected only to the previous layer containing the subset of neurons; this type of connectivity gives systems the ability to learn from the features implicitly [12].

Recurrent Neural Networks (RNNs) are ideal for processing tasks involving sequential inputs, such as Natural Language Processing (NLP) tasks (text and speech). In recurrent neural networks, the convolution layer is the most basic, but at the same time the most important layer; it convolves or multiplies a pixel array generated for the given image or object to produce an activation map for the given image [13]. The main advantage of the activation map is that it stores all the distinctive features of a given image and at the same time reduces the amount of data to be processed; unfortunately, there is also a problem in this neural network architecture: the storage of past information for a long time, i.e., long-term dependencies.

Long Short-Term Memory (LSTM) Neural Networks are a particular type of recurrent neural network that emerged to overcome the problem of recurrent neural networks with explicit memory since it uses special hidden nodes or units to remember the parameters in input form for a long time. In the literature, it is also possible to find a particular type of neural network called Bidirectional Long Short-Term Memory (Bi-LSTM) Neural Network, which consists of two regular long-short term memory networks: one with a forward direction and the other in the opposite direction.

In the current research in the literature it is common to find more complex neural networks; these make use of combinations of various neural network architectures, as some combinations are suitable to solve specific problems; the resulting architecture of the combinations is often called Deep Reinforcement Learning (DRL) [14].

2.3.2. Attention Mechanism in Neural Networks

Methods inspired by nature have been widely explored as efficient tools for solving real-world problems. In this sense, human attention mechanism could be ideally implemented through algorithms built from the synthesis of biological processes as a goal to reach a symmetry between attention inspired ANN and human auditory attention.

By the way, the attention mechanisms used in deep learning originated as an improvement to the encoder-decoder architecture used in natural language processing. Later, this mechanism and its variants were applied to other areas such as computer vision and speech processing. Before the attention mechanisms, the encoder-decoder architecture was based on stacked units of artificial neural networks of recurrent type and Long Short-Term Memory (LSTM).

The encoder (LSTM type neural network) is in charge of processing the input data and encoding them into a context vector (the last hidden state of the LSTM). It is expected this vector be a collection or summary of the input data since this vector is the initial hidden state of the decoder (intermediate encoder states are discarded); in other words, the encoder reads the input data and tries to make sense of it before summarizing them. The decoder (comprised of recurring units or LSTM) takes the context vector and produces the output data in sequential order.

As part of neural network architecture, attention mechanisms dynamically highlight the relevant features of the input data. The central idea behind the attention mechanism is not to discard the intermediate states of the encoder but to use them to build the context vectors required by the decoder to generate the output data, calculating a distribution of weights in the input sequence, and assigning higher values to the most relevant elements, and lower weights to the less relevant elements [2].

2.4. Speech

As human physiology allows for life in an air-based atmosphere, it was inevitable that humans would develop a form of communication based on acoustic signals that support the movement of molecules in the air [15]. For humans, communication through speech implies:

- The physiological properties of sound generation in the vocal system.
- The mechanisms for processing speech in the auditory system.
- The configurations imposed by the various languages.

In today's era, speech communication is no longer a process exclusive to humans. Advances in computerized speech processing allow for the continued development of technologies that attempt to improve the communication between humans and computer systems with ever-increasing performance. The challenges for speech processing in which the scientific community focuses its most significant dedication are: (i) speech recognition, (ii) language identification, (iii) emotion recognition, and (iv) speech enhancement.

Typically, these areas are studied separately; that is, researchers usually work on these specific areas to improve the performance of systems concerning systems that integrate the current state of the art, but in reality, the problem they face is the same: finding a way to

extract, represent and process the information contained in speech signals. Table 1 lists the objectives of the speech processing areas most studied by the scientific community.

Table 1. Objectives of the speech processing areas.

Speech Processing Area	Objective
Speech Recognition	Determine the content of the speech signals.
Speech Emotion Recognition	Know the emotional state of a person.
Language Identification	Identify the language or dialect of a speech signal.
Speech Enhancement	Remove background noise from the degraded speech without distorting the clean speech, thereby improving the speech quality and intelligibility.
Speaker Recognition	Recognize the identity of a person from a speech signal.
Disease Detection	Detect a specific disease from a speech signal.

3. Methodology

We planned and conducted this study based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement [1] (we adapted the items in the checklist to research in Computer Science, which differs from medical research). It is important to note that the PRISMA statement involves systematic reviews and meta-analysis. This study only does a systematic review to provide a compilation of what is available in the literature. Before performing the systematic review, we conducted a pilot test with ten randomized publications to standardize the process and resolve doubts. We discussed and resolved the differences that arose.

3.1. Protocol And Registration

The objectives, methods, strategies and analysis applied in this systematic review were carried out according to the specifications of the systematic review protocol entitled: “Attention-Inspired Artificial Neural Networks for Speech Processing: Systematic Review Protocol” as established in PRISMA-P [16]. This protocol was written, validated and approved by all authors before the systematic review.

3.2. Eligibility Criteria

The inclusion and exclusion criteria used in this systematic review are as follows.

Inclusion criteria:

- Publications made between the years 2000 and 2020.
- Publications in English.
- Publications proposing models based on artificial neural networks.
- Publications using an attention-based approach.
- Publications that consider speech applications.

We selected the time range from 2000 to 2020 to have a historical context of the last two decades to cover all those papers that implement attention.

Exclusion criteria:

- Publications that use neural network models, but do not apply them to speech.
- Publications applied to speech, but not using neural network models.
- Publications that do not use attention-based approaches.
- Publications without evaluation methods or metrics.
- Publications without clear information about their origin (authors’ affiliation and name of the journal or conference where it was published).

3.3. Information Sources

In this systematic review, the following digital libraries were used to search for publications:

- ACM Digital Library

- IEEE Explorer
- Science Direct
- Springer Link
- Web of Science

The search for publications was carried out during October 2020.

3.4. Search

The search strategy implemented in this systematic review consisted of two different steps: (i) the definition of the terms or keywords, and (ii) the definition of the search strings for each digital library.

First, we identified seven terms: comput*, model, neural network, speech, audi*, selecti* and attention; and 14 related words (words that share the same grammatical base, or synonyms): computer, computational, model, modeling, NN, deep learning, voice, speaker, audio, auditory, selective, selection, attention-based, and attention mechanism. After trying different structures, search strings for each digital library were generated, as shown in Table 2.

Table 2. Search strings.

Digital Library	Search String
ACM	Search items from: The ACM Guide to Computing Literature Title: attention OR speech Abstract: model AND attention AND (“neural network” OR “deep learning”) AND (speech OR voice) Publication Date: January 2000–October 2020
IEEE Explorer	Abstract: model AND attention AND (“neural network” OR “deep learning”) AND (speech OR voice) Filters Applied: 2000–2020
Science Direct	Find articles with these terms: model AND attention AND (“neural network” OR “deep learning”) AND (speech OR voice) Year(s): 2000–2020 Title, abstract or author-specified keywords: model AND attention AND speech
Springer Link	With all of the words: Model AND attention AND neural network AND speech With the exact phrase: neural network With at least one of the words: attention speech Where the title contains: attention Start year: 2000 End year: 2020
Web of Science	AB = (model * AND attention AND (“neural network” OR “deep learning”) AND (speech OR voice)) Year(s): 2000–2020

Some of the digital libraries allow using the asterisk (*) as a wildcard to search for words that have spelling variations or contain a specified pattern of characters. We used the asterisk (*) to find terms with the same beginning but different endings.

3.5. Study Selection

The search in the digital libraries generated a list of 902 publications. Subsequently, we carried out a filtering process to include only relevant publications in this systematic review. This process was carried out through scheduled meetings between the authors. The steps of the filtering process were as follows:

1. Remove all duplicate publications.
2. Review the title and abstract of each publication to apply the inclusion/exclusion criteria (when the information in the title and abstract was not sufficient to apply the inclusion/exclusion criteria, the full text of the publication was retrieved and reviewed).

3. Apply the quality assessment to identify publications that answered the research questions.

3.6. Data Collection Process

For the data extraction process, the researchers jointly developed a form to gather all the necessary information to answer the research questions. The form was applied separately by two of the authors, and it was reviewed by a third author. The differences of opinion that arose were discussed and resolved. It is important to mention that some publications included in the systematic review did not contain the necessary information to answer each of the items included in the form.

3.7. Data Items

The form used for data extraction contains a total of 21 items. The extracted data were divided into four general groups: (i) data on the source of the publication, (ii) data from the speech signal used, (iii) data from the deep learning models used, and (iv) details on the implementation of attention.

The individual items extracted were: digital library, type of publication, name of journal or conference, application area, publication date, publication title, names of authors, data source, features of the data used in the training, context of the original data, context of the data in the tests, language of the data, generation of the data, features extracted from the data, types of neural network used, other models used, details of the proposed model, evaluation metrics, method or process of implementing the correspondence between the model and the attention, contribution of the publication to science, and future work.

3.8. Risk of Bias in Individual Studies

In this systematic review it was considered critical to evaluate the quality of the publications to identify those that best answered the research questions. For this reason, an assessment of risk of bias (other authors refer to this study as: “quality assessment”) was applied.

For this process, 10 questions were defined to evaluate the publications; each question could obtain one of three possible answers with its respective score according to the following criteria: (i) question thoroughly answered = 1, (ii) question answered in a general way = 0.5, and (iii) question not answered = 0. The answer scores sum ranged from 1 to 10, and we selected only those publications that obtained a sum equal to or greater than 7 for the next stage of the systematic review. This evaluation was carried out by two of the authors separately and reviewed by a third researcher. The questions were:

- Q1: Is the source information clear?
- Q2: Does the publication have the primary sections of a scientific report?
- Q3: Do authors define the problem (or improvement) they address?
- Q4: Does the paper describe what the input (source) data are?
- Q5: Is the deep learning model (method) used clearly described?
- Q6: Do authors use metrics to evaluate the results?
- Q7: Is there mapping (correspondence) between the computational and biological/cognitive areas?
- Q8: Does the publication mention how attention is applied?
- Q9: Do the authors present the results in a clear way?
- Q10: In the discussion, are findings, implications, and relationship of results to other similar works considered?

The evaluation was developed based on the criteria used by the Center for Reviews and Dissemination from the University of York, published in [17].

3.9. Summary Measures

In this systematic review, we distinguished between two outcomes of interest, those considered primary (also known as primary outcomes), and those considered additional (known as secondary outcomes).

- Primary outcome: It identifies how researchers have implemented attention in neural network algorithms and the supposed correspondence between the proposal and human attention.
- Secondary outcome: It identifies the specific features extracted from the audio signals and how authors implemented them in the neural network models. Additionally, to know the areas of opportunity for future research.

4. Results

In this section are described the results obtained and the answers to the research questions of this systematic review.

4.1. Study Selection

The PRISMA-based flowchart in Figure 1 details how the review process was performed and the number of publications filtered at each stage for the final selection to be included.

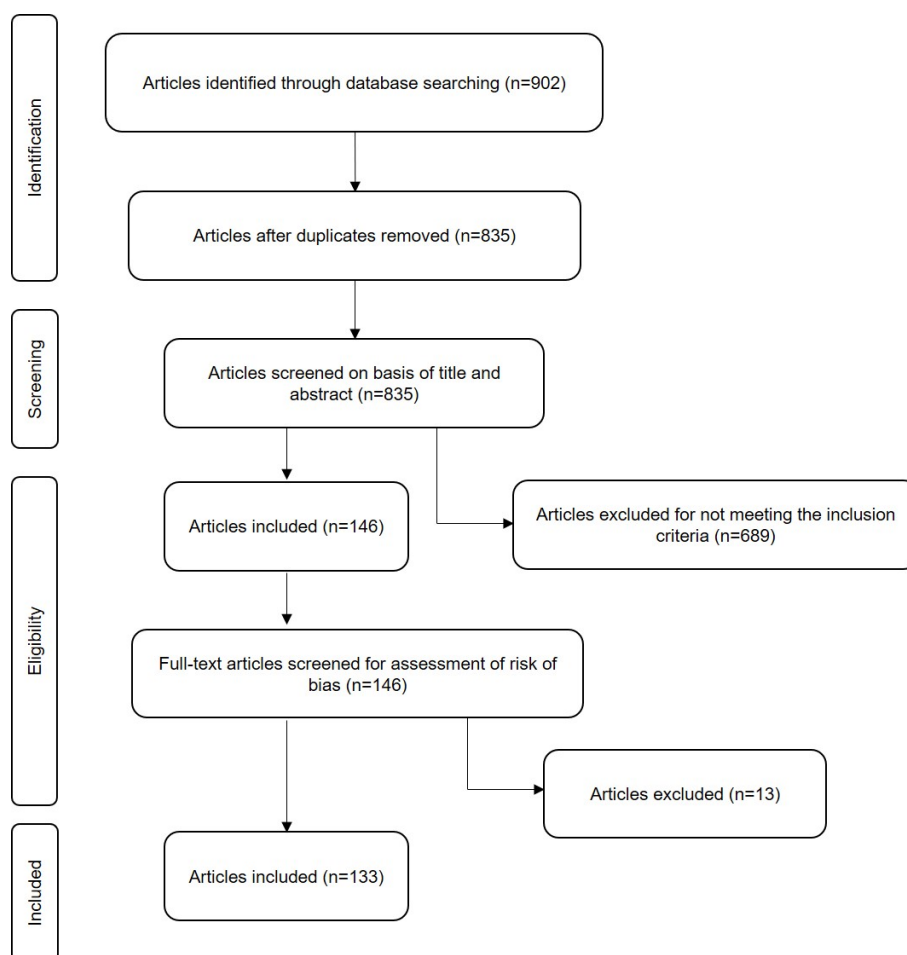


Figure 1. Flowchart of the included eligible studies in the systematic review.

4.2. Study Characteristics

Appendix A lists the publications and includes the most important data related to the research questions, which are also considered significant for this systematic review.

4.3. Risk of Bias within Studies

Appendix B contains the results of the risk assessment for bias (quality assessment) for the publications.

4.4. Results of Individual Studies

Once the information from the 133 publications selected during the systematic review was organised, different research areas were identified (as shown in Table 3) and graphically illustrated (as presented in Figure 2). The 32.3% of the publications are journal papers, and the 67.7% are conference papers. The International Conference on Acoustics, Speech, and Signal Processing (ICASSP) in its 2018, 2019, and 2020 editions were the conferences with the highest number of selected publications (36 out of 90 conference publications). Additionally, it was detected that 35.3% of the total number of publications did not include possible future work as a continuation to their research.

Table 3. Application areas identified in the publications.

Application Area	Number of Publications
Speech Recognition	47
Speech Emotion Recognition	26
Language Identification	11
Speech Enhancement	8
Speech Separation	5
Speaker Recognition	4
Speaker Verification	4
Voice Conversion	4
Disease Detection	4
Voice Activity Detection	3
Others	17

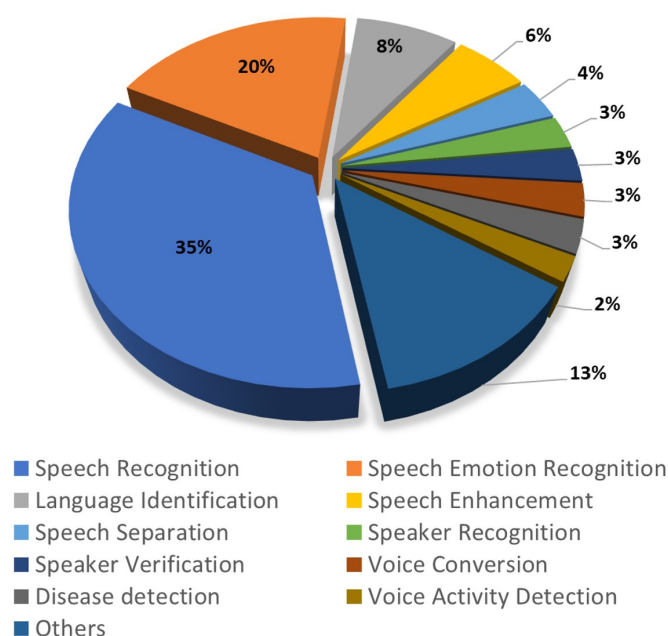


Figure 2. Distribution of the identified application areas.

Speech recognition and emotion recognition are the areas where more than half of the publications are concentrated. The "disease detection" area included publications regarding depression severity detection, dysarthria, mood disorders, and SARS-CoV-2.

In the area of "Others", there are applications with only one publication such as: adversarial examples generation, classification of phonation modes, classification of speech

utterances, cognitive load classification, detection of attacks, lyrics transcription, speaker adaptation, speech classification tasks, speech conflict estimation, speech dialect identification, speech disfluency detection, speech intelligibility estimation, speech pronunciation error detection, speech quality estimation, speech word rejection, speech-to-text translation, and word vectors generation.

Figure 3 shows the distribution of publications from 2000 to 2020. The oldest publications identified were published in 2000 and 2002 (one publication in each year). From 2003 to 2015, there were no publications identified that complied with all the requirements for inclusion. In 2016, the number of publications that met all the requirements increased substantially, being 2019 the year with the highest number of publications. Note that the number of publications in 2019 is higher than in 2020, which can be attributed to the fact that our search started in October 2020.

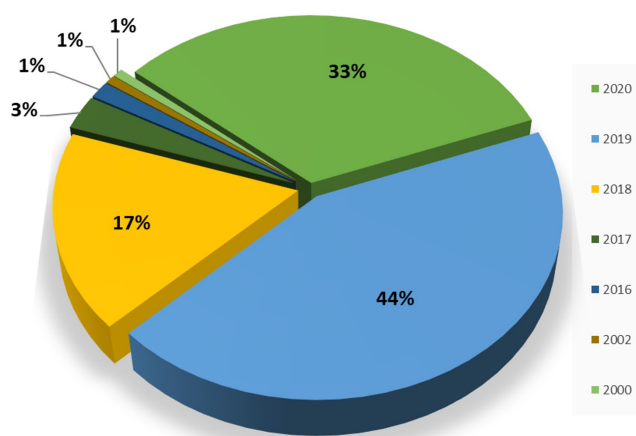


Figure 3. Distribution of publications between 2000 and 2020.

4.4.1. Answer to RQ1

After applying the inclusion/exclusion criteria and the risk assessment for bias, 133 publications were identified. Of these, 64.66% only introduce a mechanism of attention as an additional component within their neural network model. The proposed models used this mechanism to improve their performance since as mentioned by [18,19], it was found that the fusion of the neural network models and the mechanism of attention can help the models to learn where to “search” for the most significant information for the task. Thus, focusing on the relevant parts without considering the less relevant data (other terms that the authors refer to the attention mechanism are: module, layer, model, or block).

A 30.08% of the publications mention the use of an attention mechanism, but with more details or variations of this mechanism, as is the case of Bayesian attention layer [20], Multi-head Self-attention mechanism [21], or Monotonic attention mechanism [22]. In another 2.26% of the publications, it was found the application of the concept of attention in a different way than the publications that introduce a mechanism of attention. For example: in [23] they use an environment classification network as attention switch; in [24] they combine the benefits of several approaches using a language model based on attention, and in [25] they propose a selective attention strategy for the acceleration of learning in multi-layer perceptual neural networks.

The remaining 3% are publications that propose models based on neural networks with different approaches and degrees of correspondence to human attention. Specifically, Ref. [26] proposes an auditory attention model with two modules for the segregation and localization of the sound source. On the other hand, Ref. [27] proposes a selective attention algorithm based on Broadbent’s “early filtering” theory; Ref. [28] proposes a Top-Down auditory attention model. Finally, Ref. [29] improve the performance of its neural network

model for emotion recognition based on the mechanism of auditory signal processing and human attention.

4.4.2. Answer to RQ2

Training and testing of models based on artificial neural networks require sufficient and diverse data. In general, the most used datasets within the publications included in this systematic review are: (i) the Wall Street Journal corpus, (ii) the LibriSpeech corpus, and (iii) the TIMIT corpus; with presence in 11.3%, 10.5%, and 7.5% of the publications, respectively.

Regarding the features extracted from the audio files of the different datasets, the most used features are: (i) the Mel Frequency Cepstral Coefficients (MFCC), used in 25% of the publications; (ii) the Log-Mel filterbank, used in 16% of the publications; and (iii) the spectrograms, used in 13% of the publications. The sampling rate used in the audio files during the training was 16 kHz in 25.6% of the publications; 8 kHz in 4.5% and other sampling rates or multiple sampling rates in 4.5%. The most frequent languages used in the datasets are English, Mandarin, and Japanese; only 59.4% of the publications provide information about the language of the data used.

In terms of information that the authors did not find in all the publications reviewed, note the following with respect to features extracted, sampling rate and gender of the speech: (i) in 6.8% of the publications it was not found which were the features extracted from the data, (ii) in 65.4% of the publications there was no mention about the sampling rate used in models, and (iii) only 28.6% of the publications mention information about the gender of the speech in the datasets.

4.4.3. Answer to RQ3

Despite the different types of existing neural networks and the significant number of variations and combinations implemented in the publications, it was possible to identify the most used types of neural networks: (i) the neural network Bi-LSTM, (ii) the neural network LSTM, and (iii) the neural network CNN; used in 33.8%, 30.1%, and 25.6% of the publications, respectively.

The publications can use a single neural network or a combination of more than one model or neural network type. It was identified that 49.6% of the publications required only one type of neural network, 36.8% used at least two types, 9.8% used at least three types, and 3.8% used at least four types of neural network. Their combination is done by including layers of different types of neural networks or independent modules of a specific type of neural network that later are joined to create a more robust model.

Two interesting facts detected are: (i) that 12.8% of the publications do not mention information about the values of the hyper-parameters used in their neural network models, and (ii) that 12% of the publications used other additional models to complement the proposed neural network model, such as Gaussian Mixture Model (GMM), Convex Nonnegative Matrix Factorization (CNMF) and Hidden Markov Model (HMM).

4.4.4. Answer to RQ4

Among the techniques used to evaluate the performance of the diverse and different neural network models proposed in the publications, it was found that the most popular metric used was the Word Error Rate (WER) (used in 28.6% of the publications), followed by the Character Error Rate (CER) (used in 13.5% of the publications) and the Equal Error Rate (EER) (used in 12.8% of the publications). It was also found that 51.9% of the publications apply one metric, 37.6% use two metrics, 9.8% use three metrics, and only 0.8% use five metrics in their publication.

4.5. Synthesis of Results

It was found that 126 of the 133 publications introduce some mechanism, layer, or module of attention, which is added as an additional layer within their neural network model.

Only four publications implemented the combination of diverse techniques or algorithms to elaborate correspondence with human attention.

Regarding the data used in the research, it was found that the Wall Street Journal Corpus was the most used dataset, and MFCCs were the most commonly extracted features of the audio files. From what we observed in the publications, the sampling rates most used by the researchers are 16 kHz and 8 kHz, although more than half of the authors do not mention the sampling rate they used in their research. English, Mandarin, or Japanese are the most frequent languages in the datasets, except for language identification investigations, where the datasets contained data in at least four languages.

Despite the significant number of variations and combinations of the neural network models that implemented diverse attention mechanisms, it was possible to identify that the neural networks of Bi-LSTM type were the ones used, both as independent layers of the models or as independent modules. A point to consider is that we found publications that omitted information about the hyperparameters used, which makes it difficult to replicate the work for future comparisons.

Regarding the diverse metrics used to evaluate the performance of the proposed models, we found that the metrics vary even within each area of research in which the authors work; this makes it difficult to compare between works by having to find and implement some homologation of metrics that reflects the performance of each proposed model.

Table 4 summarizes the three most used datasets, features, models, and metrics by area of research or application.

Table 4. Summary by application area.

Application Area	Datasets	Features	Models	Metric
Speech Recognition	1. WSJ dataset	1. Log-Mel filterbank	1. Bi-LSTM	1. Word Error Rate
	2. LibriSpeech dataset	2. Mel-scale filterbank	2. LSTM	2. Character Error Rate
	3. CSJ corpus	3. Pitch	3. CNN	3. Phone Error Rate
Speech Emotion Recognition	1. EMO-DB dataset	1. MFCC	1. CNN	1. Unweighted Accuracy
	2. SAVEE dataset	2. Spectrogram	2. Bi-LSTM	2. Weighted Accuracy
	3. CASIA dataset	3. Zero-Crossing Rate	3. DNN	3. Unweighted Average Recall
Language Identification	1. AP17-OLR database	1. MFCC	1. DNN	1. Equal Error Rate
	2. NIST LRE dataset	2. Bottleneck features	2. Bi-LSTM	2. Average Detection Cost
	3. AP18-OLR database	3. I-vector	3. ResNet	3. Accuracy
Speech Enhancement	1. Noisex92 dataset	1. Spectrogram	1. CNN	1. Perceptual Evaluation of Speech Quality
	2. TIMIT dataset	2. MFCC	2. DNN	2. Short-term Objective Intelligibility
	3. CHiME dataset	3. AMS	3. LSTM	3. Log-Spectral Distance
Speech Separation	1. WSJ dataset	1. Spectrogram	1. Bi-LSTM	1. Signal to Distortion Ratio
	2. AIR database	2. AMS	2. LSTM	2. Signal to Artifact Ratio
	3. MIR-1K dataset	3. DRR	3. CNN	3. Perceptual Evaluation of Speech Quality
Speaker Recognition	1. VoxCeleb dataset	1. Spectrogram	1. CNN	1. Equal Error Rate
	2. AIShell public dataset	2. Log-Mel filterbank	2. DNN	2. Top-1 and Top-5 accuracies
	3. Free ST Chinese Corpus	3. MFCC	3. ResNets	3. Word Error Rate
Speaker Verification	1. VoxCeleb dataset	1. Energy	1. CNN	
	2. ASVspoof dataset	2. Linear filterbank	2. LSTM	1. Equal Error Rate
	3. BTAS2016 dataset	3. Log-Mel filterbank	3. Bi-LSTM	
Voice Conversion	1. CMU ARCTIC dataset	1. Mel-scale spectrograms	1. Bi-LSTM	1. Naturalness
	2. VCC2016 dataset	2. Phonetic posteriorgrams	2. CNN	2. Similarity
		3. Acoustic/raw spectral features	3. LSTM	3. Mel-Cepstral Distortion
Disease detection	1. CHI-MEI mood database	1. Fundamental frequency	1. LSTM	1. Mean Absolute Error
	2. COVID19 dataset	2. Harmonic-Noise-Ratio	2. Bi-LSTM	2. Probability of False Alarm
	3. DAICW-OZ database	3. Mel-filterbanks	3. CNN	3. Recall
Voice Activity Detection	1. TIMIT dataset	1. MFCC	1. Bi-LSTM	1. Accuracy
	2. HAVIC corpus	2. Log-Mel filterbank energies	2. LSTM	2. Area Under the Curve
	3. Noisex92 dataset	3. Multiresolution cochleagram	3. FC-NN	3. Equal Error Rate
Others	1. ASV spoof dataset	1. MFCC	1. Bi-LSTM	1. Word Error Rate
	2. BTEC corpus	2. Mel-filterbank	2. LSTM	2. Accuracy
	3. CCTV news corpus	3. Mel-Spectrogram	3. CNN	3. Equal Error Rate

The publications that establish a more significant correspondence with human attention are analyzed in Table 5.

Table 5. Analysis of the publications that had correspondence with human attention.

Item	[26]	[28]	[29]	[27]
Application area	Speech Separation	Speech Separation	Speech Emotion Recognition	Speech word rejection
Summary.	Presents an auditory attention model for locating and extracting a target speech in a multi-source environment. It uses two modules: One module to extract features and segregate the speech, and another module for source location.	It presents a Top-Down auditory attention model to select and separate individual speech from an audio signal. The model consists of two modules: a Bottom-Up inference module, and a Top-Down attention module. First, it generates the spectrogram of the original mix, then it predicts the number of speeches in the mix with the bottom-up inference module, then it uses the Top-Down module to extract one of the speeches, and finally, the resulting spectrogram will replace the original mix. To extract another speech, the process is repeated, until there are no speeches left in the spectrogram	It is based on the mechanism of processing auditory signals and human attention and proposes a system of emotion recognition that combines a front-end based on auditory perception and a back-end based on attention.	It proposes a selective attention algorithm based on Broadbent's "early filtering" theory, adding an attention layer in front of the input layer (of the multi-layer perception-type neural network) that works as a data filter.
Process.	First, it extracts the characteristics, then it separates the speech with a neural network, then it locates the source using the reverberation times, and finally, it identifies the nearby audio sources.	Both modules (Bottom-Up inference and Top-Down attention) are Bi-LSTM-type neural networks.	Use the back-end to extract features that include information on variations in intensity, duration, and periodicity. The neural network is used to focus on the most salient emotional regions, extracting features with a temporal attention model.	An attention filter layer is added before the input layer.
Details of the model.	Module one is a DRNN. Module two is GMM-EM.		The front-end is a CNN-3D, and the back-end is an attention-based sliding RNN.	The neural network used is a multi-layer perception.
Comparisons with human attention performance.	(1) They propose a model of auditory attention. (2) The two modules attempt to imitate two of the functions of the human auditory system. (3) They use gamma filters and are proposed as a correspondence to the way the cochlea secretes acoustic signals based on their frequencies (in humans).	(1) They propose a model of auditory attention where they integrate the two modules that were created with correspondence to Top-Down and Bottom-Up attention.	(1) The auditory front-ends are used to functionally simulate the processing of signals in the auditory system from the cochlea to the thalamus. (2) They use the Gammachirp filterbank to imitate human hearing filters. (3) The back-ends of this system capture the emotional parts of the information of the temporal dynamics in the speech, similar to the human auditory system.	(1) They propose a model of selective attention. (2) They are based on a theory of psychological selective attention. (3) They used ZCPA characteristics motivated by the auditory periphery of mammals.
Strengths.	(1) The research proposes two modules that attempt to perform two of the functions of the human auditory system (segregate a source in complex environments and locate a source by estimating its distance). (2) By joining these modules, it is possible to reduce errors in selecting the best microphone (binaural scenario) and reduce ambiguities when identifying the desired target. (3) The characteristics and modules are completely described, as well as the results obtained with each module.	(1) The proposal seeks to imitate the human capacity to focus and separate a specific source in a complicated auditory environment. To this end, two modules are used: a Bottom-Up inference module that calculates the number of sources in the mix and extracts classification data, and a Top-Down attention module that is in charge of separating the signals. (2) The modules are based on the characteristics of human attention. (3) The modules are described in sufficient detail. (4) They mention that the model was based on cognitive science theories. (5) Its proposal can be used in other areas besides the separation of sources.	(1) This proposal is inspired by the human processing of auditory signals and the human temporal attention mechanism. (2) The choice of features attempts to simulate the way the cochlea breaks down speech signals into acoustic frequency components. (3) The modules, the operating process, and the results are described in detail.	(1) The proposal is based on a theory of cognitive psychology about filtering audio signals in the human attention system. (2) The proposal deals with the problem of filtering in noisy environments. (3) The proposal can be used in other types of network models.
Weaknesses.	The proposal imitates two of the abilities of the human auditory system, but not all the abilities of the human auditory system are considered.	Its model is weak when there are similar speeches since this confuses the Bottom-Up inference module.	The data used in the research do not contain noise, so it could be inefficient to obtain good results with a noisy audio signal (the ability to ignore noise or other sources is key in human attention).	It is the oldest proposal, so it could be considered obsolete compared to the current research because the authors separate words, then it is not functional with phrases.

5. Discussion

As mentioned at the beginning of this document, this systematic review aimed to identify and analyze publications about the design and construction of neural networks that implement some mechanism of attention for speech processing (such as Top-Down and/or Bottom-Up attention) and its possible correspondence with human attention. Attention (from the human point of view) is seen as a process of allocation of cognitive resources, which respond to some priority according to events present in the environment. On the other hand, in deep learning the attention mechanisms in neural network models are designed to assign higher values of "weights" to relevant input information and ignore irrelevant information when the values of the "weights" are lower.

After conducting the systematic review, it was determined that most of the computer models based on the use of artificial neural networks (94.74%), implement only attention

mechanisms as an additional component within the architecture of their neural network models; and only 3% of the publications propose their neural network model with some degree of correspondence with human attention.

The current similarity (regarding attention functioning) between the deep learning models reviewed and the processes studied from the perspective of cognitive psychology are few and vague; which coincides with what is mentioned by [10,30]; the attention “mechanisms” currently used in artificial neural networks are an idea that can be implemented in different ways, more than an implementation of some models of the human attention [31]. This reflects the need to establish interdisciplinary collaborations to better understand the cognitive mechanisms of the human brain, as well as to explore human cognition processing from a computational perspective to develop bio-inspired computational models that have greater adaptive capabilities in uncertain and complex environments, such as acoustic environments.

Based on the evidence collected, it is not possible to establish superiority in terms of efficiency or performance between models of artificial neural networks with built-in attention mechanisms and those that attempt to establish a correspondence to attention, selective attention, or the human auditory attention system. The lack of publications that attempt to establish real correspondences with human auditory attention systems using artificial neural network models also reflects an opportunity for future research in the area of deep learning.

Regarding the features used for speech signals, it was found that 65% of the articles did not offer information about the sampling rate used for the training of the model, which implies that it is not possible to replicate the experiments, which is an essential characteristic in scientific research.

The same happens with the models of neural networks used since in some cases only the hyperparameters used are provided partially. The two situations mentioned above make it impossible to compare the results obtained in the articles analyzed with those obtained in new research.

When analyzing the metrics used in the research works it could be noticed that even in the same area of application, these evaluation methods are heterogeneous and therefore it is difficult to compare efficiencies in the results.

To our best knowledge, no systematic reviews have been conducted focusing on the different attention mechanisms implemented in deep learning algorithms for speech processing and their correspondence with human auditory attention. We only found two reviews related to attention models, the first for text processing [2] and the second for representing data as graphs [3], which confirms our assumption that there are no reviews about the inclusion of attention in deep learning algorithms for speech processing and whether there is a relationship with human auditory attention.

Difficulties in data collection due to missing information or the heterogeneity of the metrics used in the research limited comparisons between the efficiencies of the results when implementing the mechanisms of attention. Complete information would have made it possible to mention the strengths and weaknesses of each article analyzed for the others that address the same area of application.

This systematic review was limited to include proposals inspired by auditory attention, however, it is important to take into account that visual attention is a significant complement to speech processing [30]. Thus, a future systematic review will consider research works with both types of attention to analyze the efficiency of audiovisual models.

6. Conclusions

In this systematic review, we found that ANNs for speech processing have implemented some attention mechanism to improve results. We categorized the application areas, identified the most used datasets for the studies, the most used audio features, the neural network models, and the most-used metrics by the authors. We extracted some additional

data from the publications: sampling rate, language in the dataset, hyperparameters, and number of layers in ANNs.

However, the vast majority of publications that propose models of neural networks with some focus of attention for speech processing, in practice, make little correspondence with human cognitive processes of attention. This situation leads to proposals that are still far from the broad functionality and efficiency achieved by human auditory processing, therefore, the symmetry between human biological attention and attention-inspired ANNs is an utopia yet.

In many research works, the classical attention mechanism is only a part of the proposal and performs a specific function. At the same time, new research works are increasingly complex and require more elements to have better results.

The application areas of speech processing are very diverse. The classification presented in this paper may have a subclassification, and in many cases, authors addressed specific aspects (assigning weights, selecting features) of the application (speech recognition, speech separation).

We conclude that Neural Networks are essential or relevant for speech processing and therefore are the most used. Attention mechanisms have increased in a particular way in the last three years (2018–2020), and we observe an ascending behavior in terms of the number of publications. The recent boom in artificial intelligence, the advances in algorithms, and the new capabilities of hardware make it possible for areas studied for many years to regain relevance. Furthermore, given the new conditions, better results can be obtained.

We visualize a significant increase and greater relevance of computer science research inspired by nature for speech processing. In particular, proposals for neural systems with bio-inspired intelligence approaches for speech, biomedicine, biometrics, signals and images, and other applications [32].

Among the future works of speech processing, we consider that intelligent selective filtering based on previous and real-time generated knowledge will lead to proposals that are more related to how we apply auditory attention; that is, a bio-inspired proposal leads to better results.

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Appendix A

Table A1. Publications characteristics.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[26]	2018	Speech Separation	Combination of two modules (binaural source segregation and localization of a target speech signal) to make a auditory attention model	DRNN, LSTM	TIMIT dataset, AIR database, NOIZEUS7 dataset	MHEC, MFCC, RASTA-MFCC, GFCC, GBFB, PLP, RASTA-PLP, AMS, DRR	Source to interference ratio (SIR), Source to artifacts ratio (SAR), Source to distortion ratio (SDR). Unweighted Accuracy (UA), Weighted Accuracy (WA)
[33]	2018	Speech Emotion Recognition	Attention mechanism	Bi-LSTM	IEMOCAP dataset	Mel-Spectrogram	Word Error Rate (WER)
[34]	2020	Speech-to-text translation	Multi-head Self-attention mechanism	Encoder-decoder NN	BTEC corpus, Google synthesized speech	Mel-Spectrogram	Phone Error Rate (PER), Character Error Rate (CER), Word Error Rate (WER)
[35]	2018	Speech Recognition	Attention mechanism	DBN, BN-FEN	TIMIT dataset, WSJ dataset	Mels filterbank	Signal-to-Distortion Ratio (SDR)
[28]	2018	Speech Separation	Top-Down Auditory Attention model	Bi-LSTM	WSJ dataset	Spectrogram	Mel-Cepstral Distortion (MCD), Root Mean Square Error (RMSE)
[36]	2019	Voice Conversion	Attention mechanism	Seq2seq ConvErsion NeTwork (SCENT), WaveNet	CMU ARCTIC dataset	Mel-scale spectrograms	Phone Error Rate (PER)
[37]	2018	Speech Recognition	Attention mechanism	Bi-LSTM	TIMIT dataset, Voxforge dataset	MFCC	

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[38]	2020	Language Identification	Attention mechanism	Bi-LSTM	NIST LRE dataset, RATS LID Dataset	Short-term i-vectors/ x-vectors, Bottleneck features, MFCC	Equal Error Rate (EER), Accuracy, Average Detection Cost (Cavg), Perceptual Evaluation of Speech Quality (PESQ), Short-Time Objective Intelligibility (STOI), Log-Spectral Distance (LSD)
[39]	2018	Speech Enhancement	Local attention mechanism	NS-LSTM	Recordings in Chinese	Spectrogram, MFCC, LPC	Unweighted Accuracy (UA), Weighted Accuracy (WA)
[40]	2020	Speech Emotion Recognition	Attention mechanism	CNN, LSTM, GRU	IEMOCAP dataset	Spectrogram	Accuracy
[41]	2019	Disease detection (mood disorders)	Attention mechanism	CNN, LSTM	CHI-MEI mood disorder database, MHMC emotion database	Zero-crossing rate, Root-mean-square, Fundamental frequency, Harmonic Noise-Ratio, MFCC	Root Mean Square Error (RMSE), Mean Absolute Error (MAE)
[22]	2020	Disease detection (depression severity)	Soft attention mechanism (global attention approach) and Monotonic attention mechanism	Bi-LSTM, LSTM	DAICW-OZ database	Spectrogram	Short-time objective intelligibility (STOI), Perceptual Evaluation of Speech Quality (PESQ)
[18]	2020	Speech Enhancement	Attention mechanism	CNN	TIMIT dataset, Noisex92 dataset	Spectral vectors using STFT	

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Used	Network	Data	Extracted Features	Metrics Used
[42]	2020	Speech Emotion Recognition	Attention mechanism	CNN		IEMOCAP dataset, EMO-DB dataset, FAU-AIBO Corpus, EMOVO dataset, SAVEE dataset	Spectrogram	Mean Accuracy
[43]	2019	Speech Emotion Recognition	Activation attention mechanism	CNN		FAU-AIBO Corpus, EMO-DB dataset, Airplane Behavior Corpus	Spectrogram	Unweighted Average Recall (UAR)
[44]	2020	Speech Enhancement	Attention mechanism	CNN, LSTM		TIMIT dataset, Noisex92 dataset	Spectrogram	Short-term Objective Intelligibility (STOI), Perceptual Evaluation of Speech Quality (PESQ), Scale-Invariant Signal-to-Distortion Ratio (SI-SDR)
[45]	2020	Speech pronunciation error detection	Attention mechanism	Bi-LSTM		CCTV news corpus, PSC-1176 corpus	MFCC filterbank, 3-dimensional pitch	Phone Error Rate (PER), Word Error Rate (WER), Accuracy
[23]	2020	Speech Enhancement	Use of a classification neural network to act as a multidirectional attention switch	DNN		TIMIT dataset, Noisex92 dataset	Noise-aware features using STFT	Perceptual Evaluation of Speech Quality (PESQ), Short-term Objective Intelligibility (STOI)
[46]	2017	Speech Recognition	Attention mechanism	Bi-LSTM, LSTM		WSJ dataset, CHiME dataset, HKUST dataset, CSJ corpus	MFCC filterbank	Character Error Rate (CER)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[47]	2019	Speech Recognition	Attention mechanism	Bi-LSTM, LSTM	LIEPA corpus	Sequences of phonemes from raw audio files	Accuracy, Word Error Rate (WER)
[48]	2019	Speech Emotion Recognition	Attention mechanism	Dilated CNN, Bi-LSTM	IEMOCAP dataset, EMO-DB dataset	3-D feature (the static, deltas and delta-deltas of Log-Mel spectrum filterbanks)	Unweighted Accuracy (UA)
[29]	2020	Speech Emotion Recognition	Attention mechanism	3D CNN, Bi-LSTM	IEMOCAP dataset, MSP-IMPROV dataset	MFCC, emobase2010, IS09, IS13 Com-ParE, MSF	Unweighted Accuracy (UA)
[49]	2020	Speech Emotion Recognition	Attention mechanism	HSF-DNN, MS-CNN, LLD-RNN	IEMOCAP dataset	RMSE, ZCR, fundamental frequency, HNR, MFCC	Unweighted Accuracy (UA), Weighted Accuracy (WA)
[50]	2020	Speech Emotion Recognition	Attention mechanism	CNN, Bi-LSTM	IEMOCAP dataset, RAVDESS dataset, SAVEE dataset	3D scalogram	Unweighted Average Recall (UAR)
[51]	2020	Speech Emotion Recognition	Self-attention mechanism	3D CNN LSTM	IEMOCAP dataset, EMO-DB dataset, SAVEE dataset	Log-mel spectrogram	Average Processing Time, Average Accuracy
[31]	2020	Speech Separation	Attention mechanism	CNN, Bi-LSTM	MIR-1K dataset	Spectrogram	Signal to Distortion Ratio (SDR), Signal to Interference Ratio (SIR), Signal to Artifact Ratio (SAR)
[52]	2020	Speech intelligibility estimation	Attention mechanism	LSTM	UA-Speech database	MFCC, energy of the modulation spectrum, LHMR, Three prosody-related features	Accuracy Rate, Classification Rate

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[53]	2018	Speech classification tasks	Attention mechanism	CNN	UT-Podcast corpus, CHAINS corpus, eINTERFACE corpus	Spectrograms	Recall Score, Un-weighted Average Recall (UAR)
[54]	2020	Language Identification	Attention mechanism	DNN, LSTM	AP17-OLR database, NOI-SEX dataset	Shifted delta cepstral	Equal Error Rate (EER)
[55]	2018	Language identification	Attention mechanism	DNN, DNN-WA	IIIT-H database, AP17-OLR database	MFCC	Equal Error Rate (EER)
[56]	2020	Speaker Verification	Attention mechanism	ResNet, SENet	VoxCeleb dataset, VoxCeleb dataset	Spectrograms	Equal Error Rate (EER)
[57]	2019	Language identification	Self-attention mechanism	ResNet	AP18-OLR database	MFCC	Equal Error Rate (EER)
[20]	2019	Speaker Recognition	Bayesian attention layer	DNN	NIST dataset, OpenSLR corpus, VoxCeleb dataset	NA	Equal Error Rate (EER)
[58]	2019	Voice Conversion	Multi-head Self-attention mechanism	Bi-LSTM, LSTM	CMU ARCTIC dataset	Phonetic posterior-grams	Similarity
[59]	2019	Speaker Recognition	Self-attention mechanism	CNN	THCHS30 dataset, Free ST Chinese Mandarin Corpus, AIShell public dataset	MFCC, Spectrogram	Word Error Rate (WER)
[60]	2019	Speech Recognition	Multi-headed additive attention mechanism	Bi-LSTM, LSTM	LibriSpeech dataset	Log-mel filterbank	Word Error Rate (WER)
[61]	2019	Speech Separation	Additive attention mechanism	Bi-LSTM, LSTM	WSJ0-2mix dataset	Magnitude spectrograms	Signal-to-distortion ratio (SDR)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[62]	2018	Voice Activity Detection	Attention mechanism	Bi-LSTM, LSTM	TIMIT dataset	MFCC	Equal Error Rate (EER)
[63]	2018	Speech Recognition	Attention mechanism	Bi-LSTM	CSJ corpus, JNAS corpora	Log Mel-scale filterbank, delta and acceleration coefficients MFCC, ZCR, energy, entropy of energy, spectral centroid, spectral spread, spectral entropy, spectral flux, spectral rolloff, 12D chroma vector, chroma deviation, harmonic ratio and pitch	Word Error Rate (WER)
[64]	2018	Speech Emotion Recognition	Attention mechanism	Bi-LSTM, LSTM	IEMOCAP dataset		Macro Average F-score (MAF), Macro Average Precision (MAP), Accuracy
[65]	2019	Adversarial examples generation	Attention mechanism	RNN, GRU	Data collected from a smart speaker	Mel-filterbank	False Reject Rate (FRR), False Alarm Rate (FAR)
[66]	2018	Speech Recognition	Attention mechanism	CNN, LSTM	Bi-LSTM, Callcenter dataset, Reading dataset	NA	Character Error Rate (CER)
[67]	2019	Speech Enhancement	Attention mechanism	LSTM	Musan corpus, CHIME3 dataset	Spectrograms, phase information	Perceptual Evaluation of Speech Quality (PESQ), Short-term Objective Intelligibility (STOI)
[68]	2019	Language Identification	Multi-head attention mechanism	RES-TDNN	IIITH-ILSC database	MFCC, SDC, i-vector, and phonetic	Equal Error Rate (EER)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[69]	2019	Speech Enhancement	Self-attention mechanism	Wave-U-Net	CSTR VCTK Corpus, DEMAND Database	NA	Perceptual Evaluation of Speech Quality (PESQ), Word Error Rate (WER)
[21]	2020	Speech Recognition	Multi-head Self-attention mechanism	Dynamic convolution NN	CSJ corpus, Librispeech dataset, REVERVB dataset, CHiME dataset	NA	Character Error Rate (CER), Word Error Rate (WER)
[70]	2017	Speech Recognition	Attention mechanism	Bi-LSTM, LSTM, NIN, CNN	WSJ dataset	MFCC, log Mel-spectrogram	Character Error Rate (CER)
[71]	2019	Speech Recognition	Multi-head attention mechanism	DNN	CHiME dataset	Log-Mel filterbank	Word Error Rate (WER)
[72]	2019	Voice Conversion	Attention mechanism	Another author's model (modified)	CMU ARCTIC dataset	Acoustic and raw spectral features Linear filter bank (3 kHz to 8 kHz), short-term zero-crossing rate, short-term energy	Naturalness, Similarity
[73]	2020	Speaker Verification	Soft spatial attention module	DenseNet-Bi-LSTM	ASVspoof dataset, BTAS2016 dataset		Equal Error Rate (EER)
[24]	2020	Speech Recognition	Attention mechanism	LSTM	Spoken dialog between users and digital assistants DAMP—Sing!	NA	Word Error Rate Reduction (WERR)
[74]	2020	Lyrics transcription	Self-attention mechanism	CTDNN	300 × 30 × 2 dataset	Mel-spectrogram filter banks	Word Error Rate (WER)
[75]	2019	Speech Recognition	Attention mechanism	RNN	Microsoft Cortana dataset LibriSpeech dataset, DEMAND database	Log Mel filter bank	Word Error Rate (WER)
[76]	2020	Speech Recognition	Self-attention mechanism	U-Net		MFCC	Rate of Succeed Attack (RoSA), Word Error Rate (WER)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention		Neural Network Used	Data	Extracted Features	Metrics Used
[77]	2019	Speaker Verification	Multi-head	attention	LSTM, cltLSTM, CNN, DNN	VoxCeleb dataset	Static log Mel filterbanks	Equal Error Rate (EER)
[78]	2019	Speech Emotion Recognition	Self-attention mechanism		CNN	IEMOCAP dataset	Mel-spectrograms	Unweighted Accuracy (UA), Weighted Accuracy (WA), Pearson Correlation Coefficient (PCC), Unweighted Average Recall (UAR), Weighted Average Recall (WAR)
[79]	2019	Speech Conflict Estimation	Global	additive self-attention mechanism	LSTM, CRNN	SSPNet Conflict Corpus	Raw speech waveforms	Weighted Accuracy (WA), Unweighted Accuracy (UA)
[19]	2018	Speech Emotion Recognition	Attention mechanism		Bi-LSTM	IEMOCAP dataset	Pitch, energy, zero-crossing rate, voicing probability, MFCC	Unweighted Average Recall (UAR), Top-1 and Top-5 accuracies
[80]	2018	Speech Emotion Recognition	Attention mechanism		CNN	IEMOCAP dataset, Recola database	Log-Mel filterbanks	Unweighted Accuracy (UA)
[81]	2019	Speaker Recognition	Self-attention mechanism		VGG ResNets	CNN, VoxCeleb dataset	Log-Mel filterbanks	Unweighted Accuracy (UA)
[82]	2017	Speech Emotion Recognition	Attention mechanism		CNN-LSTM	eNTERFACE-05 corpus, MUSAN corpus	Log-Mel filterbanks	Unweighted Accuracy (UA)
[83]	2019	Speech Emotion Recognition	Multi-head	Self-attention mechanism	DRN, LSTM, DNN	IEMOCAP dataset	MFCC, 1-dimensional logarithmic energy, voicing probability, HNR, logarithmic fundamental frequency, zero-crossing rate	Unweighted Accuracy (UA), F1 Scores

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[84]	2019	Speech disfluency detection	Attention mechanism	Bi-LSTM, LSTM	CSJ corpus	Mel-scale filterbank, delta and delta-delta, log-pitch	F1 Scores, Word Fragments
[85]	2020	Speech Recognition	Attention mechanism	Bi-LSTM, LSTM	CSJ corpus	Log Mel-filterbank, delta and acceleration coefficients	Character Error Rate (CER), Kana Error Rate (KER)
[86]	2019	Speech Recognition	Attention mechanism	Bi-GRU, RNN	Microsoft Cortana dataset	Log-Mel filterbank	Word Error Rate (WER), Word Error Rate Reduction (WERR)
[87]	2018	Speech Emotion Recognition	Attention mechanism	RNN, LSTM	FAU-AIBO Corpus	MFCC, root-mean-square energy, zero-crossing rate, harmonics-to-noise ratio, fundamental frequency	Unweighted Averaged (UA)
[88]	2019	Speech Emotion Recognition	Attention mechanism	CNN, DNN	Bi-LSTM, IEMOCAP dataset, KSUEmotions database	Mel-frequency filter-banks, MFCC	F1 Scores, Overall Accuracy
[89]	2019	Speech Emotion Recognition	Attention mechanism	CNN, Bi-LSTM	FAU-AIBO Corpus, CASIA dataset	MFCC	Recognition Rate
[90]	2020	Speech Recognition	Multi-head attention mechanism	pBi-LSTM	English corpus, Chinese corpus, Amdo-Tibetan corpus	Log-Mel filter bank	Phoneme Error Rate (PER)
[91]	2016	Speech Recognition	Attention mechanism	Bi-RNN	WSJ dataset	Mel-scale filterbank coefficients, energy (deltas and delta-deltas)	Character Error Rate (CER) and Word Error Rate (WER)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Used	Network	Data	Extracted Features	Metrics Used
[92]	2019	Detection of attacks	Self-attention mechanism	LCNN		ASV spoof dataset	Spectral representations, Cepstral coefficients	Equal Error Rate (EER), Tandem Decision Cost Function (T-DCF)
[93]	2019	Language Identification	Attention mechanism	GRU, RNN		LRE2017 dataset	Bottleneck features	Average Detection Cost (Cavg), Approximate Computational Time
[94]	2020	Speech Recognition	Attention mechanism	Transformers		WSJ dataset	Log-Mel filterbank coefficients (with pitch and their delta and delta), raw waveform audio signal	Word Error Rate (WER)
[95]	2019	Speech Recognition	Attention mechanism	Bi-LSTM		Tibetan Ando dialect corpus (made by authors)	Mel-scale filterbank coefficients, pitch	Character Error Rate (CER)
[96]	2019	Speech Recognition	Attention mechanism	Bi-LSTM, LSTM		LibriSpeech dataset	Power-mel filterbank coefficients, Speech waveform	Word Error Rate (WER)
[97]	2019	Classification of speech utterances	Attention mechanism	DNN, CNN, Bi-LSTM		Dataset made by authors	Mel-filterbank coefficients	Detection Error Tradeoff (DET), Equal Error Rate (EER)
[98]	2018	Language identification	Attention mechanism	Bi-GRU, CNN&GRU.		Dataset made by authors	Log-Mel filter bank	Accuracy, Unweighted Average Recall (UAR)
[99]	2020	Speaker Recognition	Attention mechanism	CNN		VoxCeleb dataset	Spectrograms	Equal Error Rate (EER)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[100]	2020	Speech quality estimation	Attention mechanism	CNN-LSTM	Multiple datasets	Log-mel spectrograms	Root Mean Square Error (RMSE)
[101]	2020	Speech Recognition Emotion	Attention mechanism	Bi-LSTM	IEMOCAP dataset	Spectrogram	Unweighted Average Recall (UAR), Weighted Average Recall (WAR)
[102]	2020	Speech Recognition Emotion	Multi-head Self-attention mechanism	CNN	IEMOCAP dataset	MFCC	Unweighted Average (UA), Weighted Average (WA)
[103]	2018	Speech Recognition	Attention mechanism	VResTDCTC	CSJ corpus	Non-spliced filterbank features	Word Error Rate (WER)
[104]	2018	Speech Recognition	Attention mechanism	RNN	Dataset made by authors	NA	Word Error Rate (WER)
[105]	2019	Speech Recognition	Attention mechanism	Another author's model	LibriSpeech dataset	NA	Word Error Rate (WER)
[106]	2019	Speech Recognition	Attention mechanism	BiRNN, LSTM	Dataset made by authors	Pitch, delta, pitch	Character Error Rate (CER)
[107]	2017	Speech Recognition	Attention mechanism	Bi-LSTM, LSTM, RNN, CNN	WSJ dataset, CSJ Corpus, HKUST dataset, VoxForge dataset	Filterbank, pitch	Character Error Rates (CER), Accuracies/Error Rates
[108]	2019	Disease detection (dysarthria)	Attention mechanism	LSTM	TORGO database	Mel-filterbanks, Time-Domain filterbanks	Unweighted Average Recall (UAR)
[109]	2016	Speech Recognition	Attention mechanism	pBi-LSTM	Google voice search utterances	Log-mel filterbank	Word Error Rate (WER)
[110]	2019	Word vectors generation	Attention mechanism	RNN, Bi-LSTM	LibriSpeech dataset	MFCC	Word Similarity
[111]	2020	Speech Recognition Emotion	Multi-head mechanism	Transformer	IEMOCAP dataset	Log-Mel filterbank Energies	Weighted Average (WA), Unweighted Average (UA)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Used	Network	Data	Extracted Features	Metrics Used
[112]	2019	Language Identification	Multi-head Self-attention mechanism	DNN		AP17-OLR database	Shifted delta cepstral features (computed using MFCC)	Equal Error Rate (EER)
[113]	2019	Speech Separation	Attention mechanism	Bi-LSTM		TSP corpus, THCHS-30 dataset	Amplitude spectrum	Perceptual Evaluation of Speech Quality (PESQ), Short-term Objective Intelligibility (STOI)
[114]	2020	Voice Activity Detection	Attention mechanism	Bi-LSTM		Dataset made by authors	Log-Mel filterbank energies	F1 Scores, Accuracy
[115]	2019	Language Identification	Attention mechanism	CNN, ResNet	VD-CNN,	Dataset made by authors	Waveforms (mean-variance normalized)	F1 Scores, Accuracy
[116]	2018	Speech Recognition	Attention mechanism	DNN, CNN-LSTM		CSJ corpus	Mel-scale filterbank	Character Error Rate (CER)
[117]	2019	Voice Conversion	Self-attention mechanism	CNN		VCC2016 dataset, Data collect of internet	Mel-Cepstral Coefficients, logarithmic fundamental frequency, aperiodicity	Speaker/Singer Identity, Naturalness
[118]	2018	Speaker adaptation	Attention mechanism	RNN		Switchboard (SWB) task	PLP features	Word Error Rate (WER)
[119]	2020	Speech Recognition	Attention mechanism	Bi-LSTM, CNN		Switchboard (SWB) task, AISHELL-2 task	PLP features	Word Error Rate (WER), Word Error Rate Reduction (WERR)
[120]	2019	Speech Enhancement	Self-attention mechanism	FCNN		VCTK speech dataset	NA	Perceptual Evaluation of Speech Quality (PESQ), CSIG, CBAK, COVL, Segmented SNR

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[121]	2020	Classification of phonation modes	Attention mechanism	CNN, RAN	Four different datasets	Mel-scaled magnitude spectrum	F1 Scores, Accuracy
[122]	2020	Disease detection (SARS-CoV-2)	A self-supervised attention-based transformer	Transformer	COVID19 dataset, Librispeech dataset	Mel-scaled frequencies	F1 Scores, Recall (sensitivity), Probability of False Alarm (PFA)
[123]	2019	Speech Recognition	Self-attention mechanism	Self-attention network	HKUST dataset, CasiaMTS dataset	Filterbanks (with delta and delta-delta) Log-Mels (with delta and delta-delta transforms), i-vectors	Character Error Rate (CER)
[124]	2019	Speech Recognition	Attention mechanism	CNN, RNN	BN-6000 Corpus	Log-Mel spectrogram	Word Error Rate (WER)
[125]	2019	Speaker Verification	Attention mechanism	CNN, GRU	Tencent wake-up word dataset	Zero-Crossing Rate, Energy, Entropy of Energy, Spectral Centroid, Spectral Spread, Spectral Entropy, Spectral Flux, Spectral Rolloff, MFCC, Chroma Vector, Chroma Deviation	Equal Error Rate (EER)
[126]	2020	Speech Emotion Recognition	Attention mechanism	CNN, Bi-LSTM	Berlin dataset, DaFEx dataset, CASIA dataset	Spectral Entropy, Spectral Flux, Spectral Rolloff, MFCC, Chroma Vector, Chroma Deviation	Emotion-Wise Accuracy
[127]	2019	Speech Emotion Recognition	Self-attention mechanism	DNN, CNN	IEMOCAP dataset, RAVDESS dataset	MFCC (and energy augmented by delta and delta-delta), Log-spectrogram, eGeMAPS	Unweighted Accuracy (UA)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Used	Network	Data	Extracted Features	Metrics Used
[128]	2018	Speech Recognition	Attention mechanism	RNN		CHiME dataset, WSJ dataset	log-Mel filterbank	Word Error Rate (WER), Signal-to-Distortion Ratio (SDR), Perceptual Evaluation of Speech Quality (PESQ)
[129]	2019	Speech Recognition	Attention mechanism	DNN, LSTM, Bi-LSTMP		LibriSpeech dataset, TED-LIUM dataset, WSJ dataset	Mel scale filterbank, 3 pitch features	Word Error Rate (WER)
[130]	2019	Speech Emotion Recognition	Attention mechanism	CNN, LSTM		CASIA dataset	Spectrograms	Precision, Recall, F1 Scores
[131]	2019	Speech Recognition	Self-attention mechanism	TD-NN		LibriSpeech dataset	High resolution MFCC, i-vectors	Word Error Rate (WER)
[132]	2018	Speech Recognition	Multi-head mechanism	LSTM		Google voice search traffic	Log-Mel features	Word Error Rate (WER), Word Error Rate Reduction (WERR)
[133]	2020	Speech Recognition	Self-attention mechanism	CNN, RNN, Transformer		LibriSpeech dataset	Log-mel spectral energies, pitch information	Word Error Rates (WER)
[134]	2019	Speech Recognition	Attention mechanism	LSTM, TDLSTM		WSJ dataset, LibriSpeech corpus, HKUST dataset	Log-Mel spectral energies, pitch feature	Word Error Rates (WER)
[135]	2020	Speech Recognition	Self-attention mechanism	Transformer, RNN-T		LibriSpeech dataset	Log-Mel energy values	Word Error Rates (WER)
[136]	2019	Speech Recognition	Attention mechanism	CNN, LSTM	Bi-LSTM,	WSJ dataset, LibriSpeech corpus, HKUST dataset	Log-Mel spectral energies	Character Error Rate (CER), Word Error Rates (WER)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Network Used	Data	Extracted Features	Metrics Used
[137]	2019	Language Identification	Self-attention mechanism	DCNN, Bi-LSTM	NIST LRE dataset	Log-Mel filterbank energies	Average Detection Cost (Cavg), Equal Error Rate (EER)
[138]	2018	Voice Activity Detection	Attention mechanism	FC-NN, LSTM	TIMIT dataset, Noisex92 dataset, HAVIC corpus	Multiresolution cochleagram features (MRCG)	Area Under the Curve (AUC)
[139]	2019	Speech Recognition	Attention mechanism	DCNN	WSJCAM0 corpus, MC-WSJ-AV corpus	MFCC, Phoneme-based bottleneck feature	Word Error Rate (WER)
[140]	2019	Speech Recognition	Attention mechanism	DNN, LSTM	BLSTM, TIMIT dataset, WSJ dataset, LibriSpeech dataset	Mel filterbanks (with delta and delta-delta components)	Phone Error Rate (PER), Word Error Rate (WER)
[141]	2020	Language Identification	Attention mechanism	DNN	NIST LRE dataset, MUSAN dataset, RIR dataset	MFCC	Average Detection Cost (Cavg), Equal Error Rate (EER)
[142]	2020	Speech Emotion Recognition	Attention mechanism	RNN, DNN	IEMOCAP dataset, EmotAsS dataset	Set of prosodic features (Duration, Energy, F0 and its dynamics, Voice quality), MFCC	Weighted Average Recall (WAR), Unweighted Average Recall (UAR)
[143]	2020	Speech Recognition	Attention mechanism	LSTM, BLSTM	TED-LIUM dataset	Log-Mel f-bank features	Character Error Rate (CER), Word Error Rate (WER)
[144]	2019	Speech dialect Identification	Attention mechanism	DNN	Chinese dialects speech database	Prosodic features (F0, Energy, Loudness, Pitch), I-vector	Equal Error Rate (EER)
[25]	2002	Speech Recognition	Performing partial computation guided by attention criterions	MLP	Speech isolated-words	Coefficients derived from mel-scale filter banks	Learning Time (sec)

Table A1. Cont.

Pub	Year	Area	Form of Implementation of Attention	Neural Used	Network	Data	Extracted Features	Metrics Used
[145]	2020	Speech enhancement	Self-attention mechanism	DNN		Voice Bank Corpus database, Chinese Mandarin Test CD, Noisex92 dataset, PNL 100 Non-speech database	MFCC, AMS, RASTA-PLP, cochleagram, PNCC	Perceptual Evaluation of Speech Quality (PESQ), Short-term Objective Intelligibility (STOI)
[146]	2020	Speech Recognition	Attention mechanism	LSTM, ResNet	Bi-LSTM,	HAVRUS corpus, VoxForge dataset, M-AILABS corpus	NA	Character Error Rate (CER), Word Error Rate (WER)
[147]	2019	Cognitive Load Classification	Attention mechanism	LSTM		CSLE database	Log-Mel filterbank energies	Unweighted Average Recall (UAR)
[148]	2019	Speech Recognition	Attention mechanism	Bi-LSTM, VggCNN	LSTM,	ATC corpus	Mel-scale filterbank coefficients, pitch features	Character Error Rate (CER), Sentence Error Rate (SER)
[149]	2019	Speech Recognition	Attention mechanism	CNN, LSTM, Bi-LSTM, MLP		VoxForge dataset, M-AILABS corpus, SPIIRAS corpus	Spectrogram, filterbank, deltas features	Character Error Rate (CER), Word Error Rate (WER), Real-Time Factor (RTF).
[150]	2020	Speech Recognition	Attention mechanism	Bi-LSTM, LSTM		VoxForge dataset	MFCC, pitch features	Character Error Rate (CER)
[27]	2000	Speech word rejection	Inclusion of an attention layer	MLP		A isolated-word database	Zero Crossing with Peak Amplitude	In-vocabulary Rejection Rate, Out-of-vocabulary Rejection Rate
[151]	2020	Speech Recognition	Attention mechanism	RNN, GRU		TIMIT dataset, WSJ dataset	Mel scale filterbank, energy	Word Error Rate (WER), Phone Error Rate (PER)
[152]	2019	Speech Emotion Recognition	Self-attention mechanism	DNN, CNN, LSTM, ELM	Bi-	IEMOCAP dataset	Spectrogram	Accuracy

Appendix B

Table A2. Assessment of risk of bias.

Publication	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Final Score
[26]	1	1	1	1	1	1	1	0.5	1	0.5	9
[33]	1	1	1	1	1	0.5	0	1	1	1	8.5
[34]	1	1	1	1	1	1	0	1	1	0	8
[35]	1	0.5	1	1	1	1	0	1	1	0	7.5
[28]	1	0.5	1	1	1	1	1	1	1	0	8.5
[36]	1	1	1	1	1	1	0	1	1	0	8
[37]	1	1	1	0.5	1	1	0	1	1	0.5	8
[38]	1	1	1	1	1	1	0	1	1	0.5	8.5
[39]	1	0.5	1	1	1	1	0	1	1	0.5	8
[40]	1	0.5	1	0.5	1	0.5	0	1	1	0.5	7
[41]	1	1	1	1	1	1	0	1	1	0	8
[22]	1	1	1	1	1	1	0	1	1	1	9
[18]	1	1	1	1	1	1	0	1	1	0.5	8.5
[42]	1	0.5	1	1	1	1	0	1	1	0	7.5
[43]	1	0.5	1	1	1	1	0	1	1	0	7.5
[44]	1	0.5	1	1	1	1	0	1	1	0	7.5
[45]	1	1	1	1	1	1	0	1	1	1	9
[23]	1	0.5	1	1	1	1	0	1	1	0.5	8
[46]	1	1	1	1	1	1	0	1	1	0.5	8.5
[47]	1	1	1	1	0.5	1	0	1	1	0.5	8
[48]	1	1	1	1	1	1	0	1	1	0.5	8.5
[29]	1	1	1	1	1	1	1	1	1	1	10
[49]	1	1	1	1	1	1	0	1	1	1	9
[50]	1	0.5	1	1	1	1	0	1	1	0	7.5
[51]	1	1	1	1	1	1	0	1	1	1	9
[31]	1	0.5	1	1	1	1	0	1	1	0	7.5
[52]	1	0.5	1	1	1	1	0	1	1	0	7.5
[53]	1	1	1	1	1	1	0	1	1	1	9
[54]	1	1	1	1	1	1	0	1	1	0.5	8.5
[55]	1	0.5	1	1	1	1	0	1	1	0.5	8
[56]	1	0.5	1	1	1	1	0	1	1	0	7.5
[57]	1	1	1	1	1	1	0	1	1	0	8
[20]	1	1	0.5	0.5	0.5	1	0	1	1	0.5	7
[58]	1	0.5	1	1	1	1	0	1	1	0	7.5
[59]	1	0.5	1	1	1	1	0	1	1	0	7.5
[60]	1	0.5	1	1	1	1	0	1	1	0	7.5
[61]	1	0.5	1	1	1	1	0	1	1	0	7.5
[62]	1	0.5	1	1	1	1	0	1	1	0	7.5
[63]	1	0.5	1	1	1	1	0	1	1	0	7.5
[64]	1	0.5	1	1	1	1	0	1	1	0.5	8
[65]	1	0.5	1	1	0.5	1	0	1	1	0	7
[66]	1	1	1	1	0.5	1	0	1	1	0.5	8
[67]	1	0.5	1	1	1	1	0	1	1	0	7.5
[68]	1	1	1	1	1	1	0	1	1	0.5	8.5
[69]	1	0.5	1	1	1	1	0	1	1	0	7.5
[21]	1	1	1	0.5	0.5	1	0	1	1	0.5	7.5
[70]	1	0.5	1	1	1	1	0	1	1	0	7.5
[71]	1	0.5	1	1	1	1	0	1	1	0	7.5
[72]	1	0.5	1	1	1	1	0	1	1	0	7.5
[73]	1	1	1	1	1	1	0	1	1	0.5	8.5

Table A2. Cont.

Publication	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Final Score
[24]	1	0.5	1	0.5	1	1	0	1	1	0	7
[74]	1	1	1	1	0.5	1	0	1	1	0	7.5
[75]	1	0.5	1	1	1	0.5	0	1	1	0	7
[76]	1	1	1	1	1	1	0	1	1	0.5	8.5
[77]	1	0.5	1	1	1	1	0	1	1	0.5	8
[78]	1	1	1	1	1	1	0	1	1	0.5	8.5
[79]	1	0.5	1	1	1	1	0	1	1	0.5	8
[19]	1	0.5	1	1	1	1	0	1	1	0	7.5
[80]	1	0.5	1	1	1	1	0	1	1	0.5	8
[81]	1	0.5	1	1	1	0.5	0	1	1	0	7
[82]	1	1	1	1	1	1	0	1	1	0.5	8.5
[83]	1	0.5	1	1	1	1	0	1	1	0.5	8
[84]	1	0.5	1	1	1	1	0	1	1	0	7.5
[85]	1	0.5	1	1	0.5	1	0	1	1	0	7
[86]	1	0.5	1	1	1	1	0	0.5	1	0	7
[87]	1	0.5	1	1	1	1	0	1	1	0	7.5
[88]	1	0.5	1	1	1	1	0	1	1	0	7.5
[89]	1	0.5	1	1	1	0.5	0	1	1	0	7
[90]	1	1	1	1	1	1	0	1	1	0.5	8.5
[91]	1	0.5	1	1	1	1	0	1	1	0	7.5
[92]	1	1	1	1	1	1	0	1	1	0.5	8.5
[93]	1	1	1	1	1	1	0	1	1	0.5	8.5
[94]	1	0.5	1	1	1	1	0	1	1	0	7.5
[95]	1	0.5	1	1	1	1	0	1	1	0	7.5
[96]	1	0.5	1	1	1	1	0	1	1	0	7.5
[97]	1	0.5	1	1	1	1	0	1	1	0	7.5
[98]	1	1	1	1	1	1	0	1	1	0.5	8.5
[99]	1	0.5	1	1	1	0.5	0	1	1	0	7
[100]	1	1	1	1	1	1	0	1	1	0	8
[100]	1	1	1	1	1	1	0	1	1	0	8
[102]	1	0.5	1	1	1	1	0	1	1	0	7.5
[103]	1	0.5	1	1	1	1	0	1	1	0	7.5
[104]	1	0.5	1	1	1	1	0	1	1	0	7.5
[105]	1	0.5	1	1	0.5	1	0	1	1	0.5	7.5
[106]	1	0.5	1	1	1	1	0	1	1	0	7.5
[107]	1	0.5	1	1	1	1	0	1	1	0	7.5
[108]	1	0.5	1	1	1	1	0	1	1	0	7.5
[109]	1	0.5	1	1	1	1	0	1	1	0	7.5
[110]	1	0.5	1	1	1	0.5	0	1	1	0	7
[111]	1	0.5	1	1	1	1	0	1	1	0	7.5
[112]	1	0.5	1	1	1	1	0	1	1	0	7.5
[113]	1	0.5	1	1	1	1	0	1	1	0.5	8
[114]	1	0.5	1	1	1	1	0	1	1	0	7.5
[115]	1	1	1	1	1	1	0	1	1	1	9
[116]	1	1	1	0.5	1	1	0	0.5	0.5	0.5	7
[117]	1	0.5	1	1	1	1	0	1	1	0	7.5
[118]	1	0.5	1	1	1	1	0	1	1	0	7.5
[119]	1	0.5	1	1	1	1	0	1	1	0	7.5
[120]	1	0.5	1	1	1	1	0	1	1	0	7.5
[121]	1	0.5	1	1	1	0.5	0	1	1	0	7
[122]	1	1	1	1	1	1	0	1	1	1	9

Table A2. Cont.

Publication	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Final Score
[123]	1	0.5	1	1	1	1	0	1	1	0	7.5
[124]	1	0.5	1	1	0.5	1	0	1	1	0	7
[125]	1	0.5	1	1	1	1	0	1	1	0	7.5
[125]	1	1	1	1	1	1	0	1	1	0.5	8.5
[127]	1	1	1	1	1	1	0	1	1	1	9
[128]	1	0.5	1	1	1	1	0	1	1	0	7.5
[129]	1	1	1	0.5	1	1	0	1	1	0	7.5
[130]	1	0.5	1	1	1	1	0	1	1	0	7.5
[131]	1	0.5	1	1	1	1	0	1	1	0	7.5
[132]	1	0.5	1	1	1	1	0	1	1	0	7.5
[133]	1	0.5	1	1	1	1	0	1	0.5	0	7
[134]	1	0.5	1	1	1	1	0	1	1	0	7.5
[135]	1	0.5	1	1	1	1	0	1	1	0	7.5
[136]	1	1	1	1	1	1	0	1	1	0	8
[137]	1	0.5	1	0.5	1	1	0	1	1	0	7
[138]	1	1	1	1	1	1	0	1	1	0.5	8.5
[139]	1	1	1	1	1	1	0	1	1	0.5	8.5
[140]	1	1	1	1	1	1	0	1	1	1	9
[141]	1	0.5	1	1	1	1	0	1	1	0	7.5
[142]	1	0.5	1	1	1	1	0	1	1	0	7.5
[143]	1	0.5	1	1	0.5	1	0	1	1	0	7
[144]	1	0.5	1	1	0.5	1	0	1	1	0	7
[25]	1	0.5	1	0.5	1	1	0	1	1	0	7
[145]	1	0.5	1	1	1	1	0	1	1	0.5	8
[146]	1	0.5	1	1	1	1	0	1	1	0	7.5
[147]	1	0.5	1	1	1	1	0	1	1	0	7.5
[148]	1	0.5	1	1	1	1	0	1	1	0	7.5
[149]	1	0.5	1	1	1	1	0	1	1	0	7.5
[150]	1	0.5	1	0.5	1	1	0	1	1	0	7
[27]	1	0.5	1	1	0.5	1	1	1	0.5	0	7.5
[151]	1	1	1	0.5	1	1	0	1	1	0	7.5
[152]	1	0.5	1	1	1	1	0	1	1	0	7.5
[153]	1	0.5	1	0.5	0.5	1	0	1	1	0	6.5
[154]	1	0.5	1	0.5	0.5	0.5	0	1	1	0	6
[155]	1	0.5	1	0	1	0.5	0	1	1	0	6
[156]	1	0.5	1	1	0.5	0.5	0	1	1	0	6.5
[157]	1	0.5	1	0.5	0.5	1	0	1	1	0	6.5
[158]	1	0.5	1	1	1	0.5	0	1	0.5	0	6.5
[159]	1	0.5	1	0.5	0.5	0.5	0	1	1	0	6
[160]	1	0.5	1	0.5	1	1	0	0.5	1	0	6.5
[161]	1	0.5	1	1	1	0.5	0	1	0.5	0	6.5
[162]	1	0.5	1	0.5	0.5	1	0	1	1	0	6.5
[163]	1	0.5	0.5	1	0.5	1	0	1	1	0	6.5
[164]	1	0.5	0.5	1	0.5	1	0	1	0.5	0	6
[165]	1	0.5	0.5	0.5	0.5	1	0	1	1	0	6

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